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WIND TURBINE HEALTH MONITORING BASED ON ACCELEROMETER DATA

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Abstract. A structural health monitoring (SHM) system verifies the mechanical state of a structure to ensure its proper functioning and determines whether it needs some kind of maintenance. Thus, SHM for wind turbines (WT) in remote locations, as offshore, is crucial. Offshore wind farms are increasingly realized in water depths beyond 30 meters, where lattice support structures are an interesting option to withstand the severe environmental actions. In particular jackets appear to be a highly competitive substructure type with a wide range of applicability, from approximately 25 to 70 meters water depth. With no doubt, structural damage is a significant issue in these structures. Unlike on-shore structures or even shallow water structures, the access for regular monitoring and repair is not an easy option, in terms of both the cost and the accessibility. In this work, a methodology for the detection and classification of structural damages in offshore jacket-type WT is stated. The proposed method relies on the paradigm that any damage in the structure produces changes in the vibrational response. However, it is assumed that the only available excitation of the WT is the wind turbulence, so the input excitation is assumed to be unknown. Therefore, using only accelerometer information, a data driven approach for damage detection is developed. The scheme of the proposed method can be summarized in the following steps: (i) the wind excitation is simulated as a Gaussian white noise and the data coming from the WT is collected using a set of accelerometers; (ii) the raw data is arranged in matrix form and pre-processed using mean-centered group-scaling; (iii) principal component analysis (PCA) is selected as a technique to reduce the dimensionality of the data and the computing time of the next step; finally, (iv) the quadratic-kernel support vector machine (SVM) is used as a classifier. The 5-fold cross-validation technique is employed to estimate the overall accuracy and to avoid overfitting. In order to experimentally validate the proposed approach, the damage detection strategy is applied to different types of predefined damage in a small-scale structure —an experimental laboratory tower modeling an offshore-fixed jacked-type wind turbine—. The results that have been obtained for these predefined damages are included and discussed to demonstrate the reliability of the proposed approach.

1 INTRODUCTION

Offshore wind farms are seen as a key ingredient in renewable energy, and an important element in the battle against climate change. In the last ten years, the average offshore wind farm has increased in size from 79.6 MW in 2007 to 561 MW in 2018, see [1]. Accordingly, the size of offshore wind turbines has also increased. Since 2014 the average rated capacity of newly installed wind turbines has grown at an annual rate of 16%. As an example, the largest turbine in the world to date was installed offshore in the United Kingdom in 2018: two V164-8.8 MW from MHI Vestas Offshore Wind, with a rotor diameter of 164 m, that were connected at the European Offshore Wind Development Centre (EOWDC) wind farm, see [2]. The extreme size of nowadays offshore wind turbines leads to the demand for structural health monitoring (SHM) solutions on its overall structure. However, the foundation of fixed offshore wind turbines, in particular, are subject to harsh conditions including environmental loadings (wave and current), a corrosive environment, and shifts in the seabed as scouring and water depth erosion. Besides, inspection of the submerged foundation is expensive due to the difficult access and sometimes impossible due to the environmental conditions. In this case, SHM is the crux of the matter to provide an early warning of degradation and diminish operation and maintenance costs.

SHM for offshore wind turbines remains a research topic which is slowly getting into the field deployment stage, see [5]. This is due to the early stage of the technology's deployment, the additional challenge that offshore environments pose to these technologies, and associated costs to operators for hardware installation and data processing.

There are different types of foundations, according to the depth at which the wind turbine will be installed. In general, monopiles are used in installations at depths below 15 meters, gravity foundations are preferred when depth is less than 30 meters, and jackets are the used option for greater depths. This work focuses on the jacket type. These are foundations with a lattice framework that feature three or four sea bed anchoring points, which increases the levels of safety when anchoring the towers. The top of the jackets features a transition piece that is connected to the turbine shaft, while the legs are anchored to the sea bed with piles. This work proposes a complete methodology for damage detection and classification in a laboratory jacket-type offshore-fixed wind turbine model. As in [3], it is supposed that the only available excitation of the WT is the wind turbulence, so the input excitation is assumed to be unknown. Therefore, the scheme of the proposed method can be summarized in the following steps: (i) the wind excitation is simulated as a Gaussian white noise and the data coming from the WT is collected using a set of accelerometers. It is worth remarking that only output data will be used to detect damage; (ii) the raw data is pre-processed using group-scaling to simplify the computation of the principal components; (iii) PCA is selected as a technique to reduce the dimensionality of the data and the computing time of the next step; finally, (iv) the quadratic SVM classifier is used. In the end, 5-fold cross-validation technique is employed to estimate the overall accuracy and to avoid overfitting. In order to validate the proposed approach in this work, the damage detection strategy is applied to different types of predefined damage in a small-scale structure —an experimental laboratory tower modeling an offshore-fixed jacked-type wind turbine—. The results that have been obtained for these predefined damages are included and discussed to demonstrate the reliability of the proposed approach.

2 LABORATORY TOWER MODEL

The real structure used in this work is a tower model, similar to those of a wind turbine. From Figure 1 it can be seen the components of the structure: jacket, tower and nacelle. As a whole, this structure is 2.7 m high. The tower is composed of three sections joined with bolts, while the jacket is composed with several sections, all of them joined with bolts, with a torque of 12 Nm. The different studied damages are introduced in one of these sections, see Fig. 1. The top piece is 1 m long and 0.6 m width. There a modal shaker is located that simulates the nacelle mass and the environmental effects of the wind over the whole structure. Applying an electrical signal to the shaker (white noise), the vibration needed to excite the structure is created. The simulation of different wind speeds is also simulated with this shaker, by changing the amplitude of the input electrical signal, in particular multiplying it by the factor 0.5, 1, 2, and 3.

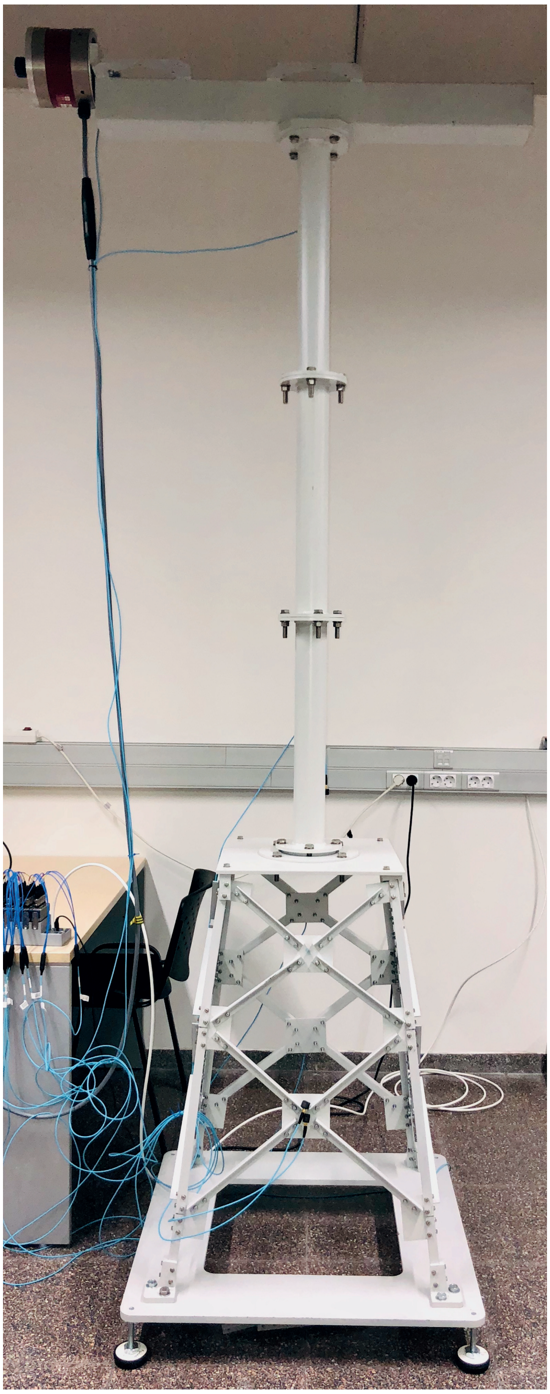

Figure 1: WT scaled tower model used in the experimental tests (off-shore fixed jacked-type platform).

Two types of damage are introduced at the jacket support: a 5 mm crack in one of the bars; and loosening one of the bolts in the jacket. Also a healthy replica of the studied bar has been considered, as the proposed strategy should be able to detect and classify the studied faults, but also be robust to the replacement of one bar by a new healthy one (avoiding false alarms).

To analyze the structural response, eight triaxial accelerometers are placed in the tower and jacket. The method used to find the optimum location and amount of these sensors is given in [4]. Thus, data from 24 sensors is collected. The nomenclature used for each sensor is given in Table 1.

Table 1: Nomenclature used to refer to each available sensor. Note that $i = 1, \dots, 8$, as there are eight accelerometers.

	Sensor
A_i^x	Acceleration in x-direction for accelerometer number i
A_i^y	Acceleration in y-direction for accelerometer number i
A_i^z	Acceleration in z-direction for accelerometer number i

3 DAMAGE DETECTION AND CLASSIFICATION METHODOLOGY

3.1 Data collection

The time window for each experimental test is 60 seconds with a sampling frequency of 1651.6129 Hz. Thus, each experiment obtains $1651.6129 \times 60 = 99097$ data measurements from each of the 24 sensors.

In this work, a total of 25 experimental tests are conducted for each different white noise amplitude. In particular:

(i) 10 tests with the original healthy bar.

(ii) 5 tests with the replica bar.

(iii) 5 tests with the 5 mm crack damaged bar.

(iv) 5 tests with an unlocked bolt in the jacket.

That is 100 experiments in total, as there are 25 experiments for each one of the 4 different considered white noise amplitudes.

Given the k-th experimental test, the data is initially stored in a matrix $\mathbf{Y}^{(k)} \in \mathcal{M}_{99097\times 24}(\mathbb{R})$ such that

$$\mathbf{Y}^{(k)} = \begin{pmatrix} y_{1,1}^{(k)} & y_{1,2}^{(k)} & \cdots & y_{1,24}^{(k)} \\ y_{2,1}^{(k)} & y_{2,2}^{(k)} & \cdots & y_{2,24}^{(k)} \\ \vdots & \vdots & \ddots & \vdots \\ y_{99097,1}^{(k)} & y_{99097,2}^{(k)} & \cdots & y_{99097,24}^{(k)} \end{pmatrix}, \tag{1}$$

where the number of rows is given by the number of time stamps in each experimental test and the number of columns is equal to the number of sensors. Note that data in the first column is related to sensor A_1^x, data in the second column is related to sensor A_1^y, third column is related to A_1^z, fourth column to A_2^x, and so on and so forth.

The data from the k-th experimental test stored initialy in matrix $\mathbf{Y}^{(k)}$, see eq. (1), is reshaped into the matrix $\mathbf{Z}^{(k)} \in \mathcal{M}_{41\times 2417\cdot 24}$,

$$\mathbf{Z}^{(k)} = \begin{pmatrix} y_{1,1}^{(k)} & \cdots & y_{2417,1}^{(k)} & \cdots & y_{1,24}^{(k)} & \cdots & y_{2417,24}^{(k)} \\ y_{2418,1}^{(k)} & \cdots & y_{4834,1}^{(k)} & \cdots & y_{2418,24}^{(k)} & \cdots & y_{4834,24}^{(k)} \\ \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ y_{96681,1}^{(k)} & \cdots & y_{99097,1}^{(k)} & \cdots & y_{96681,24}^{(k)} & \cdots & y_{99097,24}^{(k)} \end{pmatrix}, \tag{2}$$

where each row (each sample) contains 2417 time stamps from each sensor.

Finally, the data matrix $\mathbf{X} \in \mathcal{M}_{(41\cdot 100)\times(2417\cdot 24)}(\mathbb{R})$ that contains the data from all the experiments is defined by:

$$\mathbf{X} = \begin{pmatrix} \mathbf{Z}^{(1)} \\ \vdots \\ \mathbf{Z}^{(k)} \\ \vdots \\ \mathbf{Z}^{(100)} \end{pmatrix} \tag{3}$$

that is, concatenating the data matrices coming from the 100 experiments.

3.2 Autoscaling

The main reason to autoscale the raw data is to simplify the computations for the multiway PCA decomposition. Autoscaling uses column-wise mean-centering followed by division of each column by the standard deviation of that column of matrix $\mathbf{X}$. The result is that each column of the new autoscaled matrix, $\tilde{\mathbf{X}}$, has a mean of zero and a standard deviation of one. The fact that $\tilde{\mathbf{X}}$ is a mean-centered matrix simplifies the empirical covariance matrix computation, needed for the PCA decomposition.

3.3 Principal component analysis

Recall that, before using a classifier, the data must be processed to obtain the most suitable features. In this work, after the autoscaling step, multiway PCA is selected as the main objective is to reduce computing time for the quadratic discriminant analysis classifier. In this work, the first 400 components of the PCA decomposition are used as they account for 85% of the variance. Thus, the transformed coordinates of the $\tilde{\mathbf{X}}$ data in the new basis given by the first 400 principal components are used as features by the quadratic SVM strategy. Thus, 400 features are used instead of 58008 variables, that is 0.69% of the data retains 85% of the variance.

3.4 Quadratic SVM

The scatter plots shown in Fig. 2 of the first feature versus the second and tenth features reveal a quadratic relationship. Therefore, the quadratic SVM classifier is adopted. For a detailed review on the SVM classifier see references [6], [7], and [8]. In this work the kernel scale is set to 10 and the box constraint level to 2.

Finally, in this work, the 5-fold cross-validation technique has been employed to estimate the overall accuracy and to avoid overfitting.

4 RESULTS

A comprehensive decomposition of the error between the true classes and the predicted classes is shown by means of the so-called confusion matrix, see Fig. 3 (an empty blank square means 0%). In this matrix, each row represents the instances in a true class while each column represents the instances in a predicted class (by the classifier). In particular, the first row (and first column) is labeled as 1 and corresponds to the healthy and replica bar. The next labels (for rows and columns) correspond to each fault (label 2 corresponds to crack damage, and label 3 to unlocked bolt type of damage).

As shown in Fig. 3 the true positive rate (TPR) for the healthy case is 99% and the false negative rate (FNR) only 1%. For the crack damaged bar a TPR of 96% is accomplished and for the unlocked bolt type of damage a TPR of 99% is obtained. The overall accuracy is 98.6%. The training time was 1080 seconds in a 3GHz Intel Core i7 with 16GB RAM computer. Finally, note that the proposed strategy can be deployed in real time as the prediction speed is 2100 observations per second.

5 CONCLUSIONS

In this work, using only accelerometer information, a data driven approach for damage detection in offshore jacket-type WT is developed. The proposed approach has been experimentally validated for different types of predefined damages in a small-scale structure —an experimental laboratory tower modelling an offshore-fixed jacked-type wind turbine—. The obtained results, with an overall accuracy of 98.6%, demonstrate the reliability of the proposed approach.

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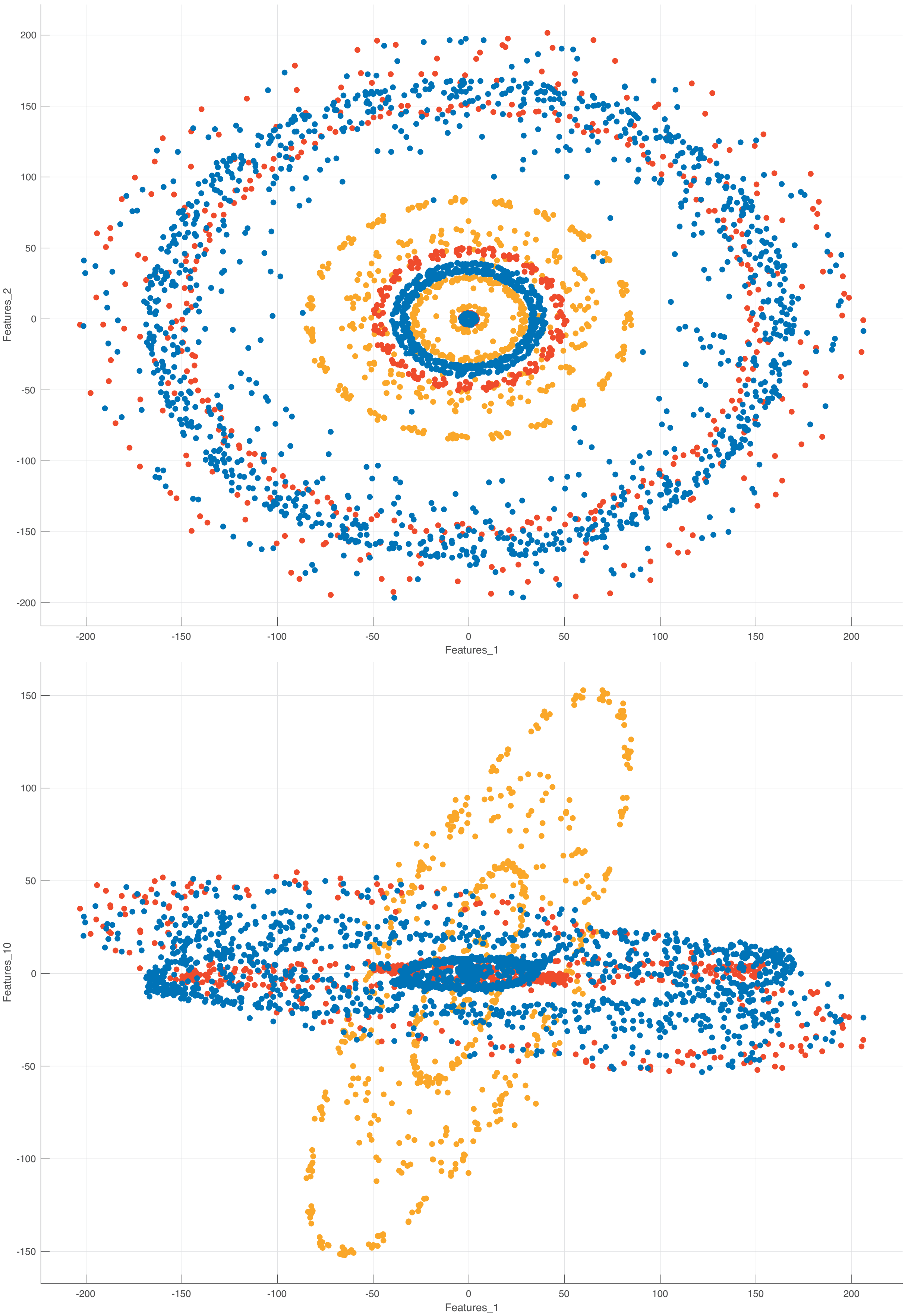

Figure 2: Scatter plots of the first versus the second feature (top) and the first versus the tenth feature (bottom). Blue dots represent healthy samples, red dots represent crack damage samples, and yellow dots represent unlocked bolt samples.

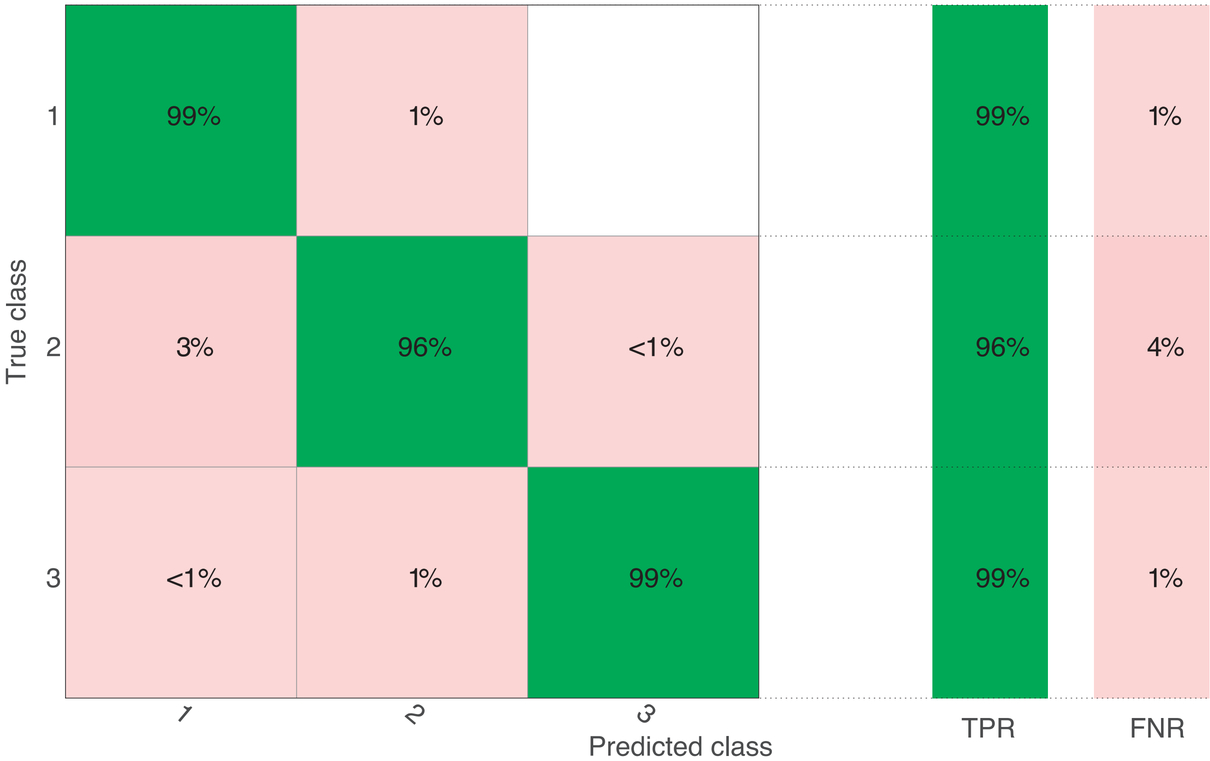

Figure 3: Confusion matrix. Label 1 corresponds to healthy, label 2 corresponds to crack damage, and label 3 to unlocked bolt type of damage.